THE DYNAMICS OF PRODUCTIVITY

IN THE

TELECOMMUNICATIONS EQUIPMENT INDUSTRY[*]

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Abstract

Technological change and deregulation have caused a major restructuring of the telecommunications equipment industry over the last two decades. We estimate the parameters of a production function for the equipment industry and then use those estimates to analyze the evolution of plant-level productivity over this period. The restructuring involved significant entry and exit and large changes in the sizes of incumbents. Since firms choices on whether to liquidate and the on the quantities of inputs demanded should they continue depend on their productivity, we develop an estimation algorithm that takes into account the relationship between productivity on the one hand, and both input demand and survival on the other. The algorithm is guided by a dynamic equilibrium model that generates the exit and input demand equations needed to correct for the simultaneity and selection problems. A fully parametric estimation algorithm based on these decision rules would be both computationally burdensome and require a host of auxiliary assumptions. So we develop a semiparametric technique which is both consistent with a quite general version of the theoretical framework and easy to use.

The algorithm produces markedly different estimates of both production function parameters and of productivity movements than traditional estimation procedures. We find an increase in the rate of industry productivity growth after deregulation. This in spite of the fact that there was no increase in the average of the plants' rates of productivity growth, and there was actually a fall in our index of the efficiency of the allocation of variable factors conditional on the existing distribution of fixed factors. Deregulation was, however, followed by a reallocation of capital towards more productive establishments (by a down sizing, often shutdown, of unproductive plants and by a disproportionate growth of productive establishments) which more than offset the other factors' negative impacts on aggregate productivity.

Keywords: Productivity, entry and exit, nonparametrics

There has been a major restructuring of the U.S. telecommunications equipment industry over the last two decades, and it can be explained, in large part, by a combination of two related factors. One was technological change which led to the development of many new products (eg. digital switching equipment and fiber optics). The other factor was a gradual liberalization of the regulatory environment (in both the provision of telecommunication services and in the use of telecommunications equipment) which culminated in the divestiture of AT&T in January of 1984. Together these changes provided many new firms, both domestic and foreign, an opportunity to enter the industry, and caused dramatic changes in the productivity of incumbents. This paper estimates the parameters of a production function for the equipment industry, and then uses those estimates to analyze changes that occurred in distribution of plant-level performance from 1974 to 1987, paying particular attention to the impact of the regulatory and technological changes on aggregate productivity. In doing so we provide both a micro framework for empirically analyzing the impact of policy (and/or environmental) changes on productivity, and an estimator for production function parameters that is consistent with a behavioral model which enables a more detailed analysis of changes in industry structure and performance.

The empirical analysis is based on an extremely rich, plant-level panel constructed from data collected by the U.S. Bureau of

the Census. It is clear from the data that during the period under investigation, the restructuring of the industry included significant entry and exit, and large changes in the size of continuing establishments. It is worth noting that related empirical work indicates that it is not uncommon to find manufacturing industries with entry, exit, and gross flow rates similar to those found in our data (this work dates back at least to Wedervang, 1965; for more recent analyses see Baldwin and Gorecki, 1988, Dunne, Roberts, and Samuelson, 1988, and Davis and Haltiwanger, 1990).

The restructuring does however highlight two estimation problems. If firms' choices on whether or not to liquidate, and on the quantities of inputs demanded should they continue, depend on productivity movements (and as we show below the data indicate that they do), the algorithm designed to estimate the parameters of the production function should take into account the relationship between productivity, on the one hand, and both survival and input demands, on the other. To guide us in building such an algorithm we introduce a dynamic model of firm behavior that allows for firm-specific sources of efficiency that evolve over time, and for entry and exit.

From the standpoint of estimation, the theoretical model provides us with a strategy for controlling for both the problem of self-selection induced by liquidation, and for the simultaneity induced by the endogeneity of the input choices (the

latter being a problem that dates back at least to the classic work of Marschak and Andrews, 1944). Direct implementation of the theoretical solution to these problems would be both computationally burdensome, and require a host of auxiliary (largely functional form) assumptions. So we develop a semiparametric estimation technique which is both consistent with a quite general version of the theoretical framework, and easy to use.

The remainder of this introduction provides a short summary of our findings. First, the theory implies that failure to control for the selection and simultaneity problems should generate very particular biases in traditional estimates of the production function parameters (biases that can explain familiar anomalies in these estimates). The empirical results verify these biases, and show that they can be very large. Indeed, in our particular case the corrected estimate of the capital coefficient is more than double that obtained through traditional estimation procedures, the corrected estimate of the labor coefficient is over thirty percent lower. The corrections also generate a noticeably different time path for aggregate productivity. The theory implies positive biases in the traditional productivity figures, and we find, in our data, the average annual bias in these figures was over a hundred percent (and the bias varied significantly from sub period to sub period).

The corrected time path for productivity still shows a doubling in the rate of aggregate industry productivity growth in the post-1984 period; from an average of .65% per year from 1974 to 1983 inclusive, to 1.2% per year from 1984 to 1987. Part of the advantage of the micro framework is that, by allowing us to disaggregate, it allows us to search for the sources of this change in productivity growth.

We show first that the increase in aggregate productivity does not seem to be the result of a more efficient allocation of variable factors conditional on the existing distribution of state variables among plants (the joint distribution of capital, productivity, and age). We define an index of variable factor allocative efficiency as the ratio of the minimum variable cost of producing the observed industry output conditional on the existing distribution of state variables, to actual variable cost of production. We find that this index actually falls in the period after deregulation. Note however, that since we expect a near monopoly to allocate production among plants to minimize the total cost of production, but do not expect such behavior from say, Nash competitors, we should not be too surprised by this finding. On the other hand, it imply that the increase in the growth rate of industry productivity that followed deregulation came from either a reallocation of fixed inputs to more productive enterprises, or from an increase in the average of plant-level rates of productivity growth.

To investigate these possibilities further we show that one can decompose the index of aggregate productivity into a sum of two terms. The first is the (unweighted) average of the productivities of the active plants, and the second is the plant-level covariance of output and productivity. The higher the covariance, the more efficient the allocation of output conditional on the plant-level distribution of productivities (i.e. allowing capital to be mobile). There is no evidence of the average productivity of the plants in the sample increasing faster in the post-1984 period. The realized productivity gains seem to be entirely a result of a reallocation of output to more productive plants. We already noted that this was not a result of a more variable factors being allocated to firms whose capital-productivity combinations warranted it. Apparently the increased competition brought with it a dramatic shift in the allocation of *capital* towards the more productive plants. This tendency is verified by computing movements in the correlation of capital and productivity over the period, and by analyzing the relationship between shutdown frequencies, on the one hand, and capital, age, and productivity, on the other. It was a result of both a down sizing (frequently the shutdown) of (often older) unproductive plants, and the disproportionate growth of productive establishments (often new entrants).

Note that the "industry's" response to the changes in its environment was a complicated dynamic process involving capital

expansion in some plants, contraction in others, and large amounts of entry and exit. A more detailed analysis of either how different primitives affected this process, or of the processes' implications on say, welfare, or on gross job flows, would require both further details on the industry (details that are currently buried in the nonparametric part of our specification), and an algorithm capable of computing the implications of the equilibrium framework that underlies our estimation technique (see Pakes and McGuire, 1991, for an example of such an algorithm).

What does seem to be clear, however, is that there were large differences among plants in their efficiency in generating sales from capital and labor expenditures and that these differences in their sales generating abilities (which we label productivity) were an important determinant of how the plants fared as a result of the regulatory and technological changes of the period. Moreover it was largely the differences in how plants of different productivities fared that determined the changes in aggregate industry performance over this period. It follows that to analyze the processes that the data singled out as being important could not (for the most part) be analyzed with aggregate data, or even with balanced panels (panels which do not include information on entrants, or on firms which eventually exit).

The first section of the paper provides a brief history of

the telecommunications equipment industry and documents some of
the relevant changes in the regulatory structure. It also
presents an overview of the data used in the analysis. Section 2
summarizes the theoretical model used to guide estimation, while
section 3 provides the estimation algorithm and presents the
parameter estimates. Section 4 uses our estimates to analyze the
evolution of industry level productivity and compares the results
implied by our procedures to those obtained from more traditional
methods of analysis. We conclude with two caveats on the
interpretation of our results. Two appendices follow. The first
discusses the data, and the second provides the variance
covariance matrix of our parameter estimates.

I   OVERVIEW OF THE INDUSTRY

We begin with a brief review of recent developments in the
telecommunications industry. This will both help to focus the
subsequent modelling exercise, and enable us to obtain a deeper
understanding of the empirical results.

Beginning in the early 1970's, the telecommunications
industry entered into a period of rapid change. The changes were
a result of a combination of significant technological
developments in telecommunications equipment and a gradual
liberalization of the regulatory environment governing the
provision of telecommunications services. Together these
developments have led to a substantial restructuring of the

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competitive environment in the U.S. telecommunications equipment industry. For the purposes of this study, we include in our definition of the industry practically all types of customer premise, and network telecommunications equipment, with the exception of the various types of transmission media, including copper wire, coaxial cable, and glass fiber (for details see the appendix).

For most of the twentieth century, American Telephone and Telegraph (AT&T) maintained an exclusive monopoly in the provision of telecommunications services and, through their procurement practices, extended that dominant position into the equipment industry.[1] This position was achieved initially by having control of the telephone patent, but AT&T's dominance in the equipment market was maintained by the requirement that any equipment that was attached to the Bell system network had to be supplied by AT&T itself. Prior to the AT&T divestiture, Western Electric, AT&T's manufacturing subsidiary, supplied approximately 90% of AT&T's equipment purchases.[2] Given the fact that AT&T was by far the largest purchaser of telecommunications equipment, entry into the equipment market was effectively prohibited.

At the manufacturing level, barriers to entry seemed to be

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[1] See Brock (1981), p.234.

[2] Office of Telecommunications (1986), p.23. Also see NTIA (1988) pp.322-323.

no greater than in other electrical appliance industries.[3] The effective barrier to entry came from restrictions in the market for users of the equipment. An end-user could not legally attach a telephone set, or any other piece of terminal equipment, to the public network. This, together with the fact that AT&T purchased equipment almost solely from Western Electric, meant that the only method of entry into the private equipment market was to establish a telephone company, a strategy that was generally prohibited by state regulatory authorities. As a result, Western Electric was relatively free from competitive pressures in the equipment market.

In recent years however, Western Electric's dominance in the equipment market has faded.[4] This is partially a result of the transition from electromechanical to fully electronic technology in both the switching and transmission of signals, a shift that has opened up many new markets for telecommunications equipment (fiber optics, digital switches, facsimile machines...). At the same time, changes in the regulatory structure governing the telecommunications industry has provided new firms the opportunity to enter the equipment industry. We turn now to a

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[3] See Brock (1981), p.235, and Temin who writes "there does not seem now nor has there been in the past an economic argument explaining why competition could not exist in the sale of telecommunications equipment," Temin (1987), p.335.

[4] This is evidenced by the fact that in 1982 the Census of Manufactures published for the first time the four-firm concentration ratio for SIC 3661, Telephone and Telegraph Apparatus. In previous years this number had been suppressed for disclosure purposes. See also NTIA (1988) pp. 305-350, and Temin (1987) for discussion of developments in the equipment industry.

brief review of the timing of these regulatory changes.

One of the first important decisions in the trend to allowing increased competition in the telecommunications equipment industry was the 'Carterphone' decision of 1968. In that case, the Carter Electronics Company won an antitrust suit against AT&T after AT&T had prevented Carter from connecting a private two-way radio system to the network. The Carterphone decision, and subsequent rulings by the Federal Communications Commission (FCC) in support of the decision, paved the way for the interconnection of private equipment to the public network.

The conditions restricting entry into the telecommunications equipment market were further eroded in 1975 when the FCC established a registration and certification program to allow for the connection of private subscriber equipment to the network, in effect extending the Carterphone decision to all equipment that met FCC standards. By 1978, the program had been extended to include PBX's, key telephone sets, and telephones. Thus the tie between the telephone service providers and the equipment industry had finally been broken.

The result of these changes was sustained entry into the U.S. telecommunications equipment industry between 1967 and 1987.[5] There was a surge in entry that began in the late 1960's and continued into the 1970's, as many small firms sought to take

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[5] There were, for example, only four PBX manufacturers in 1969, but there were over thirty of them by 1980 (National Academy of Engineering, 1984, p.86).

advantage of the Carterphone decision and the markets that opened

up as a result of the registration and certification program.

Table 1 documents this fact (for more details in the construction

of the database used in this and subsequent tables see Appendix 1

and Olley, 1991). Between 1967 and 1972 both the number of

plants and the number of firms in the industry almost doubles

and, as the table shows, there was also substantial entry between

all subsequent censuses.

Table 1

Characteristics of the Data

Year	Plants	Firms	Shipments (billions current $)	Shipments (billions 1982 $)	Employment
1963	133	104	2.587	5.865	136899
1967	164	131	3.618	8.179	162402
1972	302	240	6.222	11.173	192248
1977	405	333	11.138	13.468	192259
1982	473	375	20.319	20.319	222058
1987	584	481	25.500	22.413	184178

Though by 1982 the regulatory environment had changed

significantly, AT&T still remained the largest service provider

in the United States and, as a result, the largest purchaser of

telecommunications equipment. Consequently, as long as AT&T

continued its practice of buying most of its equipment from its

manufacturing subsidiary, Western Electric maintained a dominant

position in the equipment industry, even in the face of the

changes in the regulatory environment. The 1982 Consent Decree

changed this situation dramatically. The agreement, which was

signed in January 1982 and implemented in January 1984, called

for the divestiture of AT&T's regional operating companies. The

seven regional Bell operating companies (RBOC) that were created

from the Consent Decree are all very large companies in their own

right. For our study of the telecommunications equipment

industry it is important to note that as a result of divestiture

the RBOC's are now free to purchase equipment from any supplier

they choose, although they are prohibited from manufacturing

equipment themselves. The effect of the Consent Decree on the

purchases of equipment by Bell system companies is illustrated

rather dramatically in Table 2.

Table 2

Bell Company Equipment Procurement
(percent purchased from Western Electric)

1982	1983	1984	1985	1986[E]
92.0	80.0	71.8	64.2	57.6

E – Estimated for 1986
Source: NTIA (1988) p. 336, and discussion pp.
335–37.

Table 1 only tells part of the entire story. In addition to generating increased competition from U.S. manufacturers, the regulatory changes also induced growing competition from several large foreign producers. In both 1972 and 1977 imports accounted for only 2% of new supply, and even by 1982 that share had only reached 4%. However, the share of imports to new supply rose steadily from 1982 onwards. By 1987 imports make up fully 14% of new supply.[6] Note also that the increase in the share of imports can account for a large part of the observed fall in domestic employment between 1982 and 1987 observed in Table 1. Of course the import figures understate the share of the U.S. domestic market that the foreign suppliers were able to capture, since many of the foreign owned suppliers have established manufacturing facilities in the U.S.

Table 3 provides an indication of the overall importance of the entry process (at least in terms of domestic production). It lists the absolute number of new plants and new firms since 1972 (and since 1982), that are still active in 1987; the new plants and new firms as a percent of the total number of plants and firms active in 1987; and the shares of the new plants and the new firms in both the shipments and the employment of 1987. Almost 90% of the firms, and 80% of the plants, active in 1987

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[6] See U.S. Industrial Outlook, various years. The largest of the foreign suppliers include the Canadian firms of Northern Telecom and Mitel, Siemens from West Germany, Ericsson from Sweden, and the Japanese firms of NEC, ATI/Fujitsu, Oki, and Hitachi.

entered since 1972 and the new entities accounted for over 30% of shipments and almost 40% of employment. Indeed many of the new entrants entered after 1982 (though, as one should expect, the later entrants tended to be smaller as of 1987).[7]

Table 3:   Entrants Active in 1987

	Number	Share of Number Active in 1987 (%)	Share of 1987 Shipments (%)	Share of 1987 Employment (%)
Plants: New since 1972	463	79.0	32.8	36.0
Firms: New since 1972	419	87.0	30.0	41.4
Plants: New since 1982	306	52.0	12.0	13.5
Firms: New since 1982	299	60.1	19.4	27.5

Table 4 provides an indication of the importance of the exit or liquidation process. It provides: the fraction of plants (firms) that were active in 1972 (1982) but did not survive until 1987; the share of these entities in 1972 shipments; and their

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[7] About 400 of the 419 new entrants were "de novo" new entrants; that is they enter by opening a new plants or by transferring an existing plant into the industry. The de novo new entrants were, however, smaller in 1987 since they accounted for only 18.4% of 1987 shipments and 23.5% of employment.

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share of 1972 employment. 60% (70%) of the plants (firms) that were active in 1972 did not survive until 1987 and these plants (firms) accounted for 40.2% (13.8%) of 1972 employment and 39% (12.1%) of 1972 shipments. Indeed, over 40% of the plants that were active in 1982 did not survive until 1987, and these plants produced about 25% of 1982 output.[8]

Table 4: Incumbents Exiting By 1987

	Number	Share of Number Active in Base Year	Share of Shipments in Base Year (%)	Share of Employment in Base Year (%)
Plants active in 1972 but not in 1987	181	60.0	40.2	39.0
Firms active in 1972 but not in 1987	169	70.0	13.8	12.1
Plants active in 1982 but not in 1987	195	41.2	26.0	24.1
Firms active in 1982 but not in 1987	184	49.1	17.3	16.1

[8] There is a question of the extent to which the changes that occurred in the telecommunications equipment industry during this period induced more entry and exit (and in general more "churning") than one would typically find in a manufacturing industry. Baldwin and Gorecki, 1989, provide entry and exit figures for four digit Canadian manufacturing industries which are built from a plant level panel comparable to ours. Their figures are for a ten (rather than fifteen) year period, but when we multiply the figures they obtain as averages over all four digit industries by 3/2 to make them comparable to the figures in Tables 3 and 4 we obtain numbers for the shares of employment in new plants and firms, and the shares of employment in plants and firms that eventually exit, that are very close to ours. On the other hand, their figures for the fraction of firms that are new, and the fraction of firms initially active that eventually exit, are smaller than the analogous numbers in our tables. For a recent review of the empirical literature on entry and exit see Geroski, 1991.

Our goal in this paper is to analyze the changes in the efficiency of production and in the distribution of productivity that accompanied the changes in the regulatory and technological environment outlined in the beginning of this section. To do so, we need estimates of production function parameters. The tables in this section show that the changes in the environment were accompanied by a great deal of entry and exit, as well as significant movement in the relative sizes of the continuing establishments. These changes in size were, as one might expect, accompanied by changes in input demand, while, as we show below, a major determinant of whether or not a plant exits is its productivity. Given that a firm's productivity is not directly observable, the fact that exit and input demand decisions are based on it, generates both a selection and a simultaneity problem in obtaining production function estimates. To account for their impacts we need a model which determines both when exit occurs and how input decisions are made; a model that is rich enough to allow for firm specific, or idiosyncratic, sources of change and the equilibrating forces of entry and exit. We now turn to the task of outlining such a model.

II   THE BEHAVIORAL FRAMEWORK

In obtaining estimates of the production function parameters we are confronted with two interrelated problems. First, to the extent that differences in efficiency are known to firms when

they choose their inputs, and as we show below the efficiency of
a given firm is highly correlated over time, our attempts to
estimate production function parameters will be hindered by the
classic simultaneity problem analyzed by Marschak and Andrews
(1944).

Second, as noted above, the restructuring of the
telecommunications equipment industry during the period under
study was accompanied by a great deal of entry and exit. This
generates the issue of how to handle attrition from, and
additions to, the data during the period under study.
Traditional solutions to this problem restrict the analysis to a
"balanced" panel, studying only those firms that were present
over the entire sample period. However, if a firm's exit
decisions are made, at least in part, on the basis of their
perceptions of their productivity in the future, and if their
perceptions of their future productivity are partially determined
by realizations of their current productivity, then by
considering only those firms who survive the entire period we
will be considering a sample selected, in part, on the basis of
the unobserved productivity realizations. This in turn will
generate a selection bias of a very particular form in both the
traditional estimates of the production function parameters and
in the subsequent analysis of productivity.

To analyze either of these two problems, we need a more
detailed dynamic model of firm behavior that allows for firm-

specific efficiency differences that exhibit idiosyncratic

changes over time.[9] To sort out the simultaneity problem, the

model must specify the information available when input decisions

are made. To enable us to control for the selection induced by

liquidation decisions, the model must generate an exit rule.

There are several models that allow for idiosyncratic

uncertainty and entry and exit that are now available (see

Ericson and Pakes, 1989, Hopenhayn and Rogerson, 1989, Jovanovic,

1982, and Lambson, forthcoming). The model used here combines

certain features of the Ericson-Pakes model and the Hopenhayn-

Rogerson model. We now present a brief summary of the aspects of

those models we need in order to derive the input demand and the

liquidation rules.

As in Ericson and Pakes (1989), we assume that current

profits are a function of a vector of firm-specific state

variables and a counting measure which simply lists the vector of

state variables of all the firms' active competitors (we shall

refer to this counting measure as the market structure). In our

example, the vector of state variables consists of a_t, the age of

the firm, k_t, the firm's capital stock, and T_t, an index of the

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[9] Starting with Marschak and Andrews (1944), there is a long history of articles that recognize that one cannot evaluate alternative estimates of production function parameters without a structural model of firm behavior. Griliches, for example, writes "It is harder to make an adequate allowance for the simultaneity problem without constructing a complete production and input decision behavior model." [Griliches, 1967, pp. 277-278]. Our approach differs somewhat from the previous literature in that we use a model which is explicitly dynamic and incorporates a notion of equilibrium among firms. This allows us to account for both the changes in incumbent behavior over time and for the entry and exit observed in panel data sets.

firm's efficiency; so a market structure consists of a list of
these triples for all active firms.

At the beginning of every period an incumbent firm has three
decisions to make. The first is to decide whether to exit or
continue in operation. If it exits, it receives a sell-off value
of M dollars and never reappears again. If it continues in
operation, it chooses variable factors (labor) which, together
with the beginning period values for its state variables and,
possibly, a realization of a productivity shock, determine
current profits. In addition, the firm chooses a level of
investment, which together with the current capital value,
determines the capital stock at the beginning of the next period.

We make the following assumptions on the evolution of the
state variables. The accumulation equations for capital and age
are given by

$$k_{t+1} = (1 - {}^*)k_t + i_t \ , \tag{1}$$

and

$$a_{t+1} = a_t + 1, \tag{2}$$

both of which hold with probability one. As in Hopenhayn and
Rogerson (1990), the index of productivity, T, is assumed to be
known to the firm and to evolve over time according to an
exogenous Markov process. That is the distribution of T_{t+1} is

determined by a family of distribution functions[10]

$$P_T = \{ P(@T) , T, S \} . \tag{3}$$

The firm is assumed to maximize the expected discounted value of future net cash flows. Therefore, both the exit decision and the investment decision will depend on the firm's perceptions of the distribution of future market structures given the current information. The investment, entry, and exit decisions generated by these perceptions will, in turn, generate an actual distribution for the counting measure providing the market structure in future years. Below we simply assume the existence of a Markov Perfect Nash equilibrium in investment strategies ! an equilibrium where firms' perceptions of the distribution of future market structures are in fact consistent with the objective distribution of market structures that the firms' choices generate ! and then use the investment and liquidation rules that result from this equilibrium to help structure estimation.

In this setting, the Bellman equation for an incumbent firm can be written as,

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[10] The Ericson-Pakes (1989) model has the distribution of T_{t+1} conditional on past history dependent on the amount of investment in R&D, as well as on T_t. Unfortunately we do not have the detail on the R&D data that would make their model easy to estimate.

$$V_t(T_t,a_t,k_t) = \max \{ M, \sup_{i_t \$ 0} B_t(T_t,a_t,k_t)!c(i_t) + \$E[V_{t+1}(T_{t+1},a_{t+1},k_{t+1})^*J_t \} \qquad (4)$$

where $B_t(@)$ is the restricted profit function giving current

period profits as a function of the vector of state variables,

$c(i_t)$ is the cost of current investment i_t, $\$$ is the firm's

discount factor, and J_t represents information available at time

t. If M is greater than the second argument after the max

operator the firm exits.

Note that both the value function $V(@)$, and the profit

function $B(@)$, are indexed by t. This is to save notation. Were

we to write out either of these functions we would find that they

depend on both the market structure in the current period and on

factor prices (see Pakes and McGuire, 1990). Though these are

assumed not to vary among firms in a given period, they are free

to vary across periods, and this generates the need for the t

index on the profit and value functions (and on the policy

functions that we now derive from them).

The max operator indicates that a firm compares the sell-off

value of its plant (M) to the expected discounted returns of

staying in business until next period. If current productivity

is so low that expected profits in the future do not make

continuing in operation worthwhile, the firm closes down the

plant. If this is not the case the firm chooses an optimal

investment level (constrained to be non-negative). The solution

to this control problem generates an exit rule and an investment demand function. If we define the indicator function P_t to be equal to zero if the firm exits, then the exit rule and the investment demand equation are written, respectively, as

$$P_t = \begin{cases} 1 & \text{if } T_t \ \$ \ \underline{T}_t(a_t,k_t) \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

and

$$i_t = i_t(T_t,a_t,k_t) \ . \tag{6}$$

Note that the functions $\underline{T}_t$ and $i_t(@)$ are determined as part of the Markov Perfect Nash equilibrium, and will generally depend on all the parameters determining equilibrium behavior. Also, the fact that both these functions are indexed by t implies that both the investment rule and the liquidation decision can depend on the regulatory period (see below).

III   ESTIMATION

We assume that the industry produces a homogeneous product with Cobb-Douglas technology, and that the factors underlying profitability differences among firms are neutral efficiency differences.[11] Therefore the production function is written as

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[11]   Though we maintain the Cobb-Douglas technology assumption throughout this paper, it is easy to generalize the estimation algorithm developed below to allow for more general production technologies; translog with neutral efficiency differences across firms would, for example, do equally well. The only real limitation of the estimation algorithm is that it requires a technology that generates the invertibility condition used to go from equation (6) to (8) below (at least for some known subset of the data). This condition will be satisfied in the

$$y_{it} = \$_0 + \$_a a_{it} + \$_k k_{it} + \$_1 l_{it} + T_{it} + O_{it} \ , \qquad (7)$$

where y_{it} is the log of output (value added) from plant i at time t, a_{it} is its age, k_{it} is the log of its capital input, l_{it} is the log of its labor input, T_{it} is its productivity , and O_{it} is either measurement error (which can be serially correlated) or a shock to productivity which is independent over time. Here both T and O are unobserved. The distinction between them is that T is a state variable in the firm's decision problem, and hence a determinant of both liquidation and input demand decisions, while O is not.

Consider first the biases in the OLS estimates of (7) caused by the problems of the endogeneity of the input demands and by the self-selection induced by exit behavior. The endogeneity arises because current input choices are determined (in part) by the firm's beliefs about likely values of T_{it} when those inputs will be used. As a result, if there is serial correlation in T_{it} inputs in period t will be positively correlated with it, and an OLS procedure that fails to take account of the unobserved productivity differences will tend to provide upwardly biased estimates of the input coefficients (moreover, we expect the more variable inputs to be more highly correlated with current values of T_{it}; see Marschak and Andrews, 1944, and Griliches, 1957, for

current framework provided the marginal productivity of capital is strictly increasing in T; see Pakes, 1991, Section IV, for a more detailed exposition.

early, and more detailed, expositions).

Now consider the problem of self-selection induced by plant closings. Assuming, temporarily, that there are no variable factors (the estimation algorithm has a preliminary step which estimates their coefficients), the conditional expectation of y_t (conditional on current inputs, survival, and information available at t!1), includes the term

$$E[T_t \# a_t, k_t, T_{t!1}, P_t=1] \ .$$

Now recall that $P_t=1$ if and only if $T_t > \underline{T}_t(k_t, a_t)$. Further it is straightforward to show that the value function (equation 4) is increasing in k (and, if older firms are less productive conditional on the current value of their capital stock, decreasing in a). This implies that $\underline{T}_t(@)$ is decreasing in k (increasing in a). Firms with larger capital stocks can expect larger future returns for any given level of current productivity, and hence will continue in operation at lower T realizations. Thus, conditional on $T_{t!1}$ and observed inputs, the self-selection caused by exit behavior will cause the expectation of T_t to be decreasing in k (increasing in a), inducing a *negative* bias in the capital coefficient (and a *positive* bias in the age coefficient).[12]

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[12] The crucial part of the logic underlying the sign of these biases is that the difference between the value of continuing in operation and the sell off value of the firm be increasing in T and k, and decreasing in a. Provided this condition is met, it does not matter whether the sell off value is independent of k and a (which, for simplicity, was the specification we used in our description of the behavioral model). For similar reasons the semiparametric techniques used in the estimation algorithm do not require the sell off value of the firm to be independent of k and a.

Labor is assumed to be the only variable factor (so its choice can be affected by the current value of T_{it}). The other two inputs, k_{it} and a_{it}, are fixed factors and are only affected by the distribution of T_{it} conditional on information at time t!1 and past values of T. In particular, recall that the solution to the firm's optimization problem, (4), resulted in the investment demand equation

$$i_t = i_t(T_t, a_t, k_t) \ . \tag{6}$$

That is investment at time t as a function of the values of the three firm-specific state variables and market structure at time t.

Assume that, provided $i_t > 0$, (6) is strictly increasing in T conditional on any value for the couple, (a_t, k_t). Then (6) is invertible on the set of values for (i_t, a_t, k_t) for which $i_t > 0$, and for that set we can write

$$T_t = h_t(i_t, a_t, k_t) \ . \tag{8}$$

Since equation (8) allows us to express the unobservable productivity variable T_t, as a function of observables, it will enable us to solve the simultaneity problem. The invertibility condition that lies behind it states that, conditional on a particular value for the capital stock, firms with higher T will invest more. Regularity conditions which insure that this is true for the current example are given in Pakes (1991, section IV).

Now substitute (8) into equation (7) to obtain

$$Y_{it} = \$_l l_{it} + N_t(i_{it}, a_{it}, k_{it}) + O_{it} \qquad (9)$$

where,

$$N_t(i_{it}, a_{it}, k_{it}) = \$_0 + \$_a a_{it} + \$_k k_{it} + h_t(i_{it}, a_{it}, k_{it}) \ . \qquad (10)$$

Below we use equation (9) and a nonparametric (series) estimator of the function $N(@)$ to estimate $\$_l$. Note however, that the production function coefficients on capital and age, $\$_a$ and $\$_k$, are not identified from this equation since the equation does not allow us to separate out the effect of capital and age on the investment decision from their effect on output.

To identify the age and capital coefficients we have to use the panel structure of the data and the model's implications regarding the relationship between the observed productivities of a given firm over time. Recall that we only observe the subsequent year's data for those plants that survive, so in order to proceed we need the probability of survival. That probability is given by

$$\Pr\{P_{t+1}=1^* \underline{T}_{t+1}(k_{t+1}, a_{t+1}), J_t\} = \Pr\{T_{t+1}\$\underline{T}_{t+1}(k_{t+1}, a_{t+1})^* \underline{T}_{t+1}(k_{t+1}, a_{t+1}), T_t\}$$
$$= P_t\{\underline{T}_{t+1}(k_{t+1}, a_{t+1}), T_t\} \qquad (11)$$
$$/ \ P_t$$

where we have dropped the dependence of the variables on the individual subscript (i) for notational convenience. Together, the accumulation and the investment equations imply that both a_{t+1}

and k_{t+1} can be expressed as functions of the triple (T_t,a_t,k_t) and $T_t=h_t(i_t,a_t,k_t)$. So the probability in (11) can be expressed as a time dependent function of i_t, a_t, and k_t. Below we provide a nonparametric estimators of this survival probability.

We complete the system to be estimated by considering expectation $y_{t+1}!\$_1l_{t+1}$ conditional on inputs at time t+1 and survival. This equation, when combined with the estimates of $\$_1$, N_t, and P_t, from (10) and (11) will allow us to identify $\$_a$ and $\$_k$. We have,

$$E[y_{t+1}!\$_1l_{t+1}*a_{t+1},k_{t+1},\ P_{t+1}=1]$$

$$= \$_0 + \$_aa_{t+1} + \$_kk_{t+1} + E[T_{t+1}*T_t,\ P_{t+1}=1] \qquad (12)$$

$$= \$_0 + \$_aa_{t+1} + \$_kk_{t+1} + I \quad T_{t+1} \ \textbf{S}))))))))\textbf{Q} \atop T_{t+1} \ \ \ I\ P(dT_{t+1}*T_t) \atop \underline{T}_{t+1}$$

with $\dfrac{P(dT_{t+1}*T_t)}{I\ P(dT_{t+1}*T_t)}$ over the bracket

$$= \$_aa_{t+1} + \$_kk_{t+1} + g(P_t,T_t)$$

where

$$g(P_t,T_t) = \$_0 + I \quad T_{t+1} \ \textbf{S})))))))))\textbf{Q} \atop T_{t+1} \ \ \ I\ P(dT_{t+1}*T_t) \atop \underline{T}_{t+1}$$

with $\dfrac{P(dT_{t+1}*T_t)}{I\ P(dT_{t+1}*T_t)}$

and the last equality assumes that the function giving the probability of survival, $P_t=P_t(\underline{T}_{t+1}(k_{t+1},a_{t+1}),T_t)$, is invertible for almost every T_t, allowing us to write $\underline{T}_{t+1}(@)$ as a function of P_t and T_t.

Now note that (12) and (11) together imply that

$$y_{t+1}!\$_1l_{t+1} = \$_aa_{t+1} + \$_kk_{t+1} + g(P_t,N_t!\$_aa_t!\$_kk_t) + >_{t+1} + O_{t+1} \qquad (13)$$

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where,

$$\omega_{t+1} = T_{t+1} - E[T_{t+1}*T_t, P_{t+1}=1] .$$

Equation (13) helps clarify two points; why we need the
first stage estimation algorithm, and why we need an estimate of
T (in addition to P) to make the selection correction. First
note that the difference between T_{t+1} and its expectation
conditional on past history (including T_t) and survival, that is
ω_{t+1}, is mean independent of both k_{t+1} and a_{t+1} (since both these
variables are known functions of variables available at the
beginning of the period), but not of l_{t+1} (since labor can adjust
to realizations in current productivity). Use of the estimate of
$\$_1$ from the first stage allows us to remove this simultaneity
problem in the choice of labor by taking that variable over to
the left hand side of the estimating equation. Second note that
the exit probability depends on both T_t and on $\underline{T}_{t+1}(@)$ (which
varies across firms). As a result firms with the same exit
probabilities can have different expectations of T_{t+1} conditional
on survival.

We turn now to a brief description of the details needed to
actually implement the estimation of the system given by (9),
(11), and (13). The reader who is not interested in these
details can turn directly to our discussion of Table 6 (bottom of
page 26) where our empirical results are described.

Equation (10) is an example of one of the earliest

semiparametric regression models. It has been analyzed using

both kernel (Robinson, 1988) and series (Andrews, 1990a and

Newey, 1991b) estimators of $N_t(@)$ and, subject to regularity

conditions, the resulting estimators of $\$_1$ have the same limiting

distribution. For simplicity, we use a polynomial series

estimator for $N_t(@)$. That is we project y_t on l_t and a polynomial

in the triple (i_t, a_t, k_t). The empirical results presented here

use a fourth order polynomial (with a full set of interactions)

to approximate the $N_t(@)$ function, but there was almost no change

in either the estimates of the coefficients of interest, or the

minimand, when we went from a third to a fourth order

approximation. Also, since the investment function, and hence

$N_t(@)$, should differ with changes in market structure (see

equation 6 above), we estimated different polynomials for each of

the four regulatory periods (1974-77, 1978-80, 1981-83, and 1984-

86; see the discussion in section I)

Next we consider the estimation of the selection equation in

(12), the equation giving the probability of survival as a

function of (i_t, a_t, k_t). Here we use both a series and a kernel

estimator of the function determining the survival probability

and then compare the results. The series approximation was

constructed by using a polynomial series in (i_t, a_t, k_t) as

regressors in a probit estimation algorithm (the formula the

computer uses to compute the normal distribution is a series

approximation to the true distribution; so this gives us a series

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composed with a series as our approximating function). Again we

used a fourth order polynomial in (i_t, a_t, k_t) with a full set of

interactions, and again there was no change in the fit going from

the third to the fourth order. The kernel results that we

present here use the bias reducing normal based kernels in

Bierens (1987), though the parameter estimates were almost

identical when we used a standard normal kernel.[13] Again, since

the model implies that both the stopping rule and the investment

equation change with market structure, we ran both the kernel and

the series estimator twice; once allowing for different selection

equations in each of the four different regulatory periods, and

once not.

Table 5 provides the correlation coefficients between P_{t+1},

the indicator variable for survival in period t+1 conditional on

survival in period t, and the different estimates of the survival

probabilities. Two points come out clearly from the table.

First, the kernel estimator provides predictions (PHAT1 and

PHAT2) which fit better than the series estimator (PHAT3 and

PHAT4). Second, the fits are quite a bit better when we allow

for different stopping rules and different investment functions

in the four different regulatory regimes (compare PHAT2 to PHAT1,

or in the series case, PHAT4 to PHAT3). Consequently we use

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[13] Whenever we use the bias reducing kernels in Bierens, 1987, we use a diagonal S with the inverse of the variance of the regressors as the diagonal elements, choose a bandwidth by cross-validation, and use a degree of bias reduction of four. Standard normal kernels used a diagonal covariance matrix with the inverse of the variance of the regressors as the diagonal elements, and a bandwidth of one.

PHAT2, the kernel estimates that allow for differences in the
selection function in the different regulatory periods, in the
analysis that follows.

Table 5 :

Correlation Coefficients between Various Predicted
Survival Probabilities and P_{t+1}

	P_{t+1}	PHAT1	PHAT2	PHAT3	PHAT4
P_{t+1}	1.00	.285	.350	.102	.218
PHAT1	.285	1.00	.671	.398	.324
PHAT2	.350	.671	1.00	.215	.583
PHAT3	.102	.398	.215	1.00	.483
PHAT4	.218	.324	.583	.483	1.00

Notes:
(1) P_{t+1} is a 0,1 random variable that takes the value 0
     when a plant closes.

(2) PHAT1 and PHAT2 are the kernel estimates. PHAT1 is
     estimated over the entire data set together, and PHAT2
     is estimated separately for the four time periods,
     1974-1977, 1978-1980, 1981-1983, and 1984-1986.

(3) PHAT3 and PHAT4 are the probit estimates. PHAT3 has no
     time dummies, and PHAT4 is estimated with time period
     dummies corresponding to the time periods in note (2),
     and these dummies are interacted with i_t, k_t, and a_t.

The third (and final) step of the estimation procedure takes
the estimates of $\$_1$, N_t, and P_t from the first two steps,
substitutes them into equation (13) for the true $\$_1$, N_t, and P_t,
and then obtains estimates of $\$_a$, $\$_k$, and the g(@) function by

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minimizing the sum of squared residuals in the resulting

equation. Here we also try both a series and a kernel estimator

of the unknown function $g(P_t, h_t)$ function. Recall that it is $\mathbb{N}_t$

that we estimate, and $h_t = \mathbb{N}_t - \$_a a_t - \$_k k_t$, so that the values of

the regressors that determine $g(@)$ depend upon the values of the

parameters of interest.

For the series estimator we used a fourth order polynomial

expansion in (h_t, P_t) (and again there was almost no difference in

either the sum of squares, or in the coefficients of interest,

when we went from the third to the fourth order approximation).

Thus the series estimator is obtained by running nonlinear least

squares on the equation

$$y_{t+1} - b_l l_{t+1} = c + \beta_a a_{t+1} + \beta_k k_{t+1} + \sum_{j=0}^{4-m} \sum_{m=0}^{4} \beta_{mj} \hat{h}_t^m \hat{P}_t^j + e_t \tag{15}$$

with,

$$\hat{h}_t = \hat{\phi}_t - \beta_a a_t - \beta_k k_t \quad . \tag{16}$$

$\mathbb{N}_t$ and b_l are taken from the estimates of equation (9), and $\hat{P}_t$ is

taken from equation (11).

The kernel results were obtained by forming kernel estimates

of the regression of

$$y_{t+1} - b_l l_{t+1} - \$_a a_{t+1} - \$_k k_{t+1}$$

on the regressors

$$\hat{P}_t \text{ and } \hat{h}_t = \mathbb{N}_t - \$_a a_t - \$_k k_t$$

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for different values of ($\$_a$, $\$_k$), and then using a nonlinear

search routine to find the value of this parameter vector that

minimized the sum of squared residuals from this regression.

Again the results presented here use the bias reducing kernels in

Bierens (1987) (though we have also used a standard normal kernel

with little difference in the resulting coefficient estimates).[14]

   Finally the results indicate that a linear trend

(representing disembodied technical change) was significant, so

we included a time trend in the production function in (10), and

carried it through the entire estimation procedure.

   A note on the properties of these estimators are in order

before proceeding. Pakes and Olley (1991) provide a set of

conditions on $h_t(@)$, $p_t(@)$, $g_t(@)$, and the distribution of the data,

that insure that when we use the kernel estimator of $g(@)$ in

equation (13) we obtain consistent and asymptotically normal

estimators of the capital, age, and time coefficients (it adapts

and extends previous results by Newey, 1991b, and Andrews, 1990b,

to cover problems which require estimates of nonparametric

functions which are indexed by either other nonparametric

functions, or by the parameters of interest). Appendix 2 of this

paper uses the results in Pakes and Olley (1991) to obtain a

formula for a consistent estimator of the covariance matrix of

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[14]   The estimation procedure here was computationally more burdensome as the kernel had to be re-evaluated each time we needed to evaluate the objective function at a different parameter vector. As a result we chose the bandwidth by cross validation at the estimate of the parameter vector obtained from the series estimation procedure, and held the bandwidth fixed at that value thereafter.

our parameters. We do not currently know of a theorem that insures consistency and asymptotic normality when a series estimator is used for g(@) in equation (13). On the other hand, we would find it surprising if the series estimator did not have the same properties as the kernel estimator, and it is *much* easier to compute.

The results of the alternative three step estimation procedures, together with some other estimates of the production function coefficients, are provided in Table 6. Columns 1 and 2 obtain their estimates from the subset of data set that contains only those plants that were active throughout the entire sample period. That is, these columns use the traditional "balanced panel". Column 1 provides the OLS estimates from the balanced panel, while Column 2 provides the within estimates (the estimates from a fixed effects model which uses deviations from plant specific means as data in a least squares estimation procedure). Columns 3 to 10 use the "full" sample; this sample keeps plants that eventually drop out for all periods in which they are active, and introduces new entrants as they appear. Column 3 provides the OLS estimates from the full sample, Column 4 provides the within estimates, and column 5 adds investment to the right hand side variables and reruns the OLS procedure. Columns 6 and 7 make partial corrections to the OLS procedure (the first for selection, and the second for the serially correlated unobserved state variable; see below). Columns 8 to

10 provide different versions of our three step estimation procedure.

The first point to note from the table is that the full sample contains over two and a half times the number of observations in the balanced panel. That is, the selection criteria that is implicit in using a balanced panel throws out 60 to 70 percent of the observations in the full sample. The fact that these fractions are so large, together with the theoretical discussion which implied that the selection process should generate very particular biases in the estimates of the production function coefficients, will help clarify some of the anomalies generated by the balanced panel.

Table 6: Alternative Estimates of Production Function Parameters[1] (standard errors in parentheses)									
Sample	Balanced Panel		Full Sample[3,4]						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
									Nonparametric P_T	
Estimation Procedure	Total	Within	Total	Within	OLS	Only P	Only h	Normal P_T	Series	Kernel
Labor	.869 (.038)	.773 (.050)	.695 (.019)	.65 (.025)	.63 (.02)	.615 (.027)				
Capital	.163 (.033)	.054 (.048)	.308 (.017)	.14 (.025)	.23 (.02)	.37 (.02)	.29 (.03)	.292 (.073)	.32 (.035)	.35 (.045)
Age	.001 (.003)	-.010 (.016)	-.0048 (.0016)	-.004 (.002)	-.002 (.002)	-.006 (.002)	.001 (.005)	-.0025 (.010)	-.00 (.004)	.01 (.014)
Time	.025 (.006)	.047 (.016)	.023 (.004)	.023 (.005)	.02 (.004)	.03 (.005)	.005 (.01)	.023 (.002)	.035 (.019)	.04 (.038)
Investment	-	-	-	-	.13 (.01)	-	-	-	-	-
Other Variables Present	-	-	-	-	-	Powers of P	Powers of h	Mill's Ratio and h	Full Polynomial in P and h	Kernel in P and h
SSE (Final equation)	-	-	-	-	-	619.6	587.8	593.2	580.8	553.7
# Obs.[2]	886	886	2397	2397	2397	1603	1603	1603	1603	1603

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Notes for Table 6:

(1)   The dependent variable in columns 1 to 4 is the log of value added, while in columns 6 to 10, the dependent variable is $\log(va) - b_1 * \log(labor)$.

(2)   The number of observations in the balanced panels of regressions 1 and 2 are the observations for those plants that have continuous data over the period, with zero investment observations removed. Similarly, the 2397 observations use in columns 3,4, and 5 are all observations in the full sample except those with zero investment. Approximately 8% of the full data set had observations with zero investment. Columns 6 to 10 have fewer observations due to the fact that the sampling procedures for the ASM forced us to drop observations in years 1978, 1983, and the last year, 1986. See note 3.

(3)   The number of observations in the last five columns decreases to 1603 both because we needed lagged values of some of the independent variables in estimation, and because, due to the sampling design for the data, we could not us all the data in the last year of the rotating five-year panels that make up the Annual Survey of Manufactures. This is because we did not want to mistake missing data for some of the plants as exit, when in fact it is the result of not being sampled for the next five-year panel. To check that the estimates in columns 3,4, and 5 are not simply the result of the sample, we ran the same estimating equations on the 1603 plant sample and got almost identical results.

(4)   Consult the text for details of the estimation algorithm leading up to columns 6 to 10.

The estimates in columns 1 and 2 are what we have come to expect from production function estimates from balanced panels. The labor coefficient is higher than we would expect for the elasticity of output with respect to labor (certainly higher than the share of labor in total cost which is about .65 in this data), while the capital coefficient is lower than we would expect (it almost disappears in estimates which use the "within" dimension, see column 2).[15]

Recall that we had two reasons for worrying about biases in these estimates. First endogeneity of the input choices should lead to a positive correlation between the inputs and the unobserved productivity term (a problem which is likely to be more severe the more variable the input and hence the easier to adjust to current realizations of productivity). This is the traditional reason for believing there is a positive bias in ordinary least squares estimate of the labor coefficient. The within estimator will only account for the bias to the extent that the plant's productivity term is constant over time (and recall that this is an industry that underwent major restructuring during the period under study). Second, even considering the 1972 cross section as the universe for the subsequent analysis, by taking the balanced panel we are only keeping those firms that did well enough to survive the entire

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[15] We will not focus on either the age or the time coefficients in what follows since, though their values are generally consistent with our expectations, they are never estimated with much precision.

period (recall that Table 4 indicated that this was under half of the plants that were active in 1972). Since firms with larger capital stocks will survive on the basis of lower productivity realizations, selecting on survival generates a negative correlation between the disturbance term in the selected sample and capital.

By going to the full sample we expect to eliminate much of the selection problem, but not necessarily the problems generated by the endogeneity of the input choices. Columns 3 and 4 provide the OLS and within estimates on the full sample. The simple act of adding back in the plants that were active during only part of the sample period almost *doubles* the capital coefficient and pushes the labor coefficient down by about 20% (and this is true whether we compare the total or the within columns). Of course, both the column 3 and 4 coefficients should still be biased by both selection and endogeneity. In particular since the within column uses only changes over time and has to discard those plant-year changes in productivity that induce the plant to close down, one might expect it still to contain a large negative bias in the capital coefficient generated by selection; whereas the total column makes no attempt at all to control for firm specific differences in productivity, so we might expect it still to contain a large positive bias in the labor coefficient.

More formally, to account for the positive bias in the labor coefficient in column 3, we need to substitute a polynomial

expansion in the triple (i_t, a_t, k_t) for T_t in equation (7) and to re-estimate the equation. Column 5 adds only investment to the list of regressors in column 3. If the polynomial needed for T_t were both linear and did not require interactions with time for the different regulatory periods, the estimate of the labor coefficient in column 5 would be consistent. The capital and age coefficients, however, would confound the effect the effect of capital and age on output with their effect on investment and hence have no direct interpretation. There are two points to note from the estimates in column 5. First the investment coefficient is highly significant, indicating that there is indeed likely to be a simultaneity bias in the estimates of column 3. Second, as predicted by the theory, the labor coefficient goes down again, this time by another 10%.

The labor coefficient from equation (10), the equation that used a fourth order polynomial expansion in (i_t, a_t, k_t) whose coefficients were allowed to vary over the four regulatory periods to account for T_t, was .615 (.027) (not very different from the coefficient from column 5, and between 10 and 15% lower than the OLS coefficient on the full sample). Columns 6 to 10 use this coefficient, the implied estimate of T_t, and the estimate of P_t from the selection equation (11), to obtain the estimates of the capital, age, and time coefficients.

Column 6 regresses $y_{t+1} ! .615l_{t+1}$ on age, capital, time, and a polynomial in the estimate of the selection probability. If

there were no serial correlation in T_t, implying no endogeneity problem in this equation, use of the polynomial in the estimate of the selection probability should correct for the selectivity bias and generate consistent estimates of the coefficients of interest. On the other hand, if T is serially correlated, then we would expect k_{t+1} to be positively correlated with T_t, producing a positive bias in the capital coefficient in this column. So we would expect this column to provide us with an estimate of an upper bound to the capital coefficient.

Column 7 regresses y_{t+1} ! $.615l_{t+1}$ on age, capital, time, and a polynomial in $\hat{h}_t$, the estimate of T_t that we get from the first equation. If firms could not exit, so that there were no selectivity problem, then use of the polynomial in $\hat{h}_t$ would correct for the endogeneity problem and produce consistent estimates of the coefficients of interest. Given that even transitions on the full panel are selected for survival (though this is only survival over a two, not thirteen, year period), and the theory tells us that the selection process should generate a negative bias in the capital coefficient, we expect this column to provide an estimate of a lower bound for the capital coefficient.

The estimates of the upper and lower bounds were, respectively, .37(.02) and .29 (.03) (the standard errors of the coefficients in these columns were obtained from a bootstrap procedure). The implied interval rules out both balanced panel

estimates and the within estimates from the full sample, but
still leaves a fairly large range of possible values for the true
capital coefficient. Note also that the fact that the value of
the minimand in column 7 is much lower than that in column 6
attests to the likely empirical importance of the serially
correlated unobserved state variable that $\hat{h}_t$ proxies for.

Column 8 provides a halfway mark between the generality of
our full model and a parametric alternative. The consistency of
the estimates in this column require that P_T be given by the
parametric family

$$T_{t+1} = D\ T_t + >_{t+1}\ ,\quad \text{where } >_{t+1} - N(0,F^2)$$

and N(@) signifies a normal distribution. Briefly, it uses the
probit estimates of the selection equation to obtain a
nonparametric estimate of the truncation point in that equation
and then notes that, given the normality assumptions, the
expectation of T_{t+1} conditional on past history and survival will
depend only on T_t (estimated by $\hat{h}_t$) and Mill's ratio evaluated at
the truncation point. Columns 9 and 10 provide the series and
the kernel estimates of the version of our model which does not
restrict P_T.

The first point to note is that all three of these
procedures produce estimates of the capital coefficients that are
between the upper and lower "bounds" for this coefficient given

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in columns 6 and 7. There is some evidence that the constraint

imposed by normality produces both a lower capital coefficient

and a significantly worse fit than the more general model, so we

shall disregard column 8 in what follows. The other two

estimates are not much different from one another; and this is

true whether we use as our difference metric their estimated

standard errors or their empirical implications as discussed in

the next section (we have already done the empirical analysis of

productivity using both the column 9 and the column 10 estimates

with no significant difference in the results).[16] On the other

hand both columns are quite different from the results of the

more traditional estimation procedures discussed earlier.

IV   The Implications of Our Estimators on Productivity

This section of the paper uses our production function

estimates to construct measures of plant level productivity in

the telecommunications equipment industry and then analyzes

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[16] We have done a lot more analysis of these coefficients than is reported above, and this note reviews the other results. The system was estimated using several different estimators for the nonparametric components, and adding a trimming step to account for observations in low density regions. None of the alternative estimators generated much of a change in the coefficient estimates (the capital, age, and time coefficients varied between .31 and .35, -.01 and .01, and .01 and .04 respectively). There was one run, however, in which the estimated standard errors doubled as a result of an outlier that was trimmed in the trimming procedure. In addition we ran systems in which multiplant firms had different investment and stopping rules (we also tried differentiating by the number of plants), and investigated differences in estimates over different subperiods of the panel. The only significant (from a statistical point of view) change occurred when we split the sample into three equally sized time intervals, and re-estimated the model in the first and last of these. The results provided evidence of an increase in the capital intensity of the industry over time, as the OLS capital coefficient from the full subamples went from .27 (.03) to .34 (.03), and the estimates from the bias reducing kernel version of our procedure went from .32 (.08) to .40 (.05). Again these differences are simply not large enough to make any substantial difference to the economic implications discussed in the next section.

changes in the distribution of this productivity measure between 1974 and 1987. Our plant level productivity measure is calculated as

$$p_{it} = y_{it} ! b_l l_{it} ! b_k k_{it} ! b_a a_{it} ,$$

where the b's are taken from column 10 in Table 6.

We begin with the aggregate industry productivity. Table 7 compares two measures of aggregate industry productivity growth between 1975 and 1987. We calculate our aggregate measure (P1 in the first column) as the share-weighted average of our plant-level productivity measure, using plant-level shares of the full sample as weights.   P2 in column 2 provides the productivity growth rates derived in an analogous way but using the production function coefficient estimates and the shares of output from the balanced panel (from column 1 in Table 6). Column 3 sums the difference between P1 and P2 from the beginning of the sample period, while column 4 provides the BLS's measure of growth in aggregate manufacturing productivity (P3). Figure 1 normalizes productivity to equal 1 in 1974, and then plots the levels of our measure, and of the measure obtained from the balanced panel, over the period. The difference between the two curves in this figure is column 3 of Table 7.

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Table 7:

Industry Productivity Growth Rates

Year	1 P1	2 P2	3 $3(P1_t - P2_t)$	4 P3
1975	-.127	-.113	-.014	-.014
1976	-.017	-.030	-.001	.052
1977	.070	.073	-.004	.032
1978	.084	.089	-.009	.016
1979	.012	.005	-.002	-.007
1980	.060	.090	-.032	-.023
1981	-.001	-.003	-.036	.011
1982	.002	.017	-.051	-.005
1983	-.059	-.051	-.059	.059
1984	.044	.032	-.041	.068
1985	.047	.084	-.094	.038
1986	-.021	-.024	-.091	.027
1987	.009	.043	-.125	.034

Column 1 -   output weighted average from entire data set
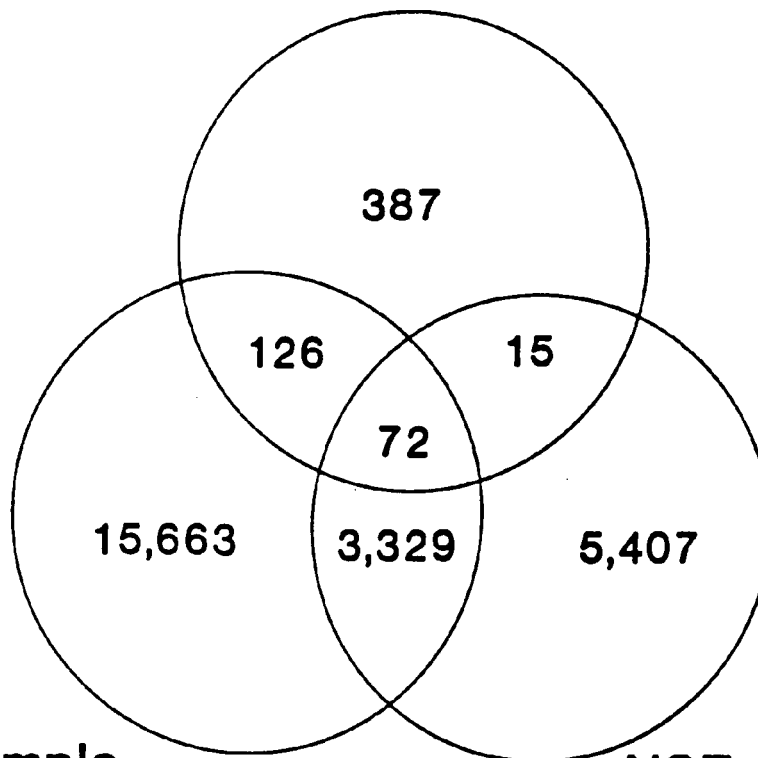   using our corrected estimates
Column 2 -   output weighted average for balanced panel
              using balanced panel estimates
Column 4 -   all of manufacturing (source: Bureau of
              Labor Statistics)

Figure 1: QFR, NSF & LBO Samples

LBO Sample: 600 LBOs

387

126   15

72

15,663   3,329   5,407

QFR Sample
18,992 Non-LBOs
198 LBOs

NSF Sample
8,736 Non-LBOs
87 LBOs

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We begin with a comparison of P1 to P2. Column 3 makes it clear that P1 drops below P2 immediately and remains below it throughout the sample period. Indeed the annual growth rate of P2 (1.63%) over the period as a whole is over double the growth rate of P1 (.79%). Recalling that the balanced panel excludes those plants which exit during the sample period, a selection which our theory tells us should delete precisely those plants with low productivity growth, the fact that P1 is lower than P2 should not be surprising. The other difference between the two samples is that the balanced panel excludes new entrants. Empirically, new entrants tended to be smaller plants with lower productivity than the average productivity of continuing establishments (but higher productivities than those plants which exit). So the difference in the treatment of new entrants between the two panels reinforces the difference between the productivity measures that is induced by the difference in the treatment of those who exit.

Note that this reasoning leads us to expect particularly large differences between the productivity measures in periods when there is disproportionate amounts of entry and exit. Column 3 shows that the difference between P1 and P2 takes a jump upward between 1979 and 1980, just after the registration and certification program, and then another discrete jump in 1985, just after divestiture. These were precisely the years where there was likely to be disproportionate amounts of entry and exit

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(see Tables 3 and 4 above, and Table 11 below). Indeed the

average annual difference between P1 and P2 in the period after

divestiture was 2.2% (3.4% versus 1.2%), almost two and a half

times the average annual difference between P1 and P2 over the

entire sample period. The lesson here is that aggregate

productivity calculations based on balanced panels can generate

large positive biases during periods when an industry is

undergoing a significant amount of restructuring.

   The extent to which the movements in P1 can be accounted for

by historical changes in the structure of the telecommunications

equipment industry is quite striking. Notice first the surges in

productivity that follow both the registration and certification

program in 1977 and 1978, and the divestiture in 1984. Also the

growth rate in productivity is practically zero in 1982, and

negative from 1982 to 1983. Given that the Consent Decree

announcing divestiture was signed in January 1982, this period

was undoubtedly a time of reorganization and restructuring for

the industry as a whole. The negative growth in productivity

probably reflects the cost of reorganization among incumbents and

the time it takes new entrants to settle into production.

   Column 4 provides annual growth rates in productivity for

all of manufacturing. Note that the two periods of high growth

rates in the telecommunications equipment industry, 1977-1978 and

1984-1985, are not reflected in the data on aggregate

manufacturing. The two periods of telecommunications

productivity growth are a result of factors that are specific to that industry (eg., regulatory changes) and are not related to trends in overall manufacturing. This comes through even more clearly in Table 8, where we provide the correlation coefficients between the three growth rate series in Table 7. The growth rate of productivity in the telecommunications equipment industry has an r^2 of almost zero with the growth rate for manufacturing as a whole.

Table 8

r^2 's for the Growth Rates reported in
Table 7

	1	2	3
1	1.00	.916	.008
2	.914	1.00	.001
3	.008	.001	1.00

We now delve deeper into the determinants of industry productivity. We first ask about the efficiency of the output allocation among plants in the industry. One can ask this question either conditional on the extant distribution of fixed factors (age, capital, and productivity), or unconditionally. We begin by considering the efficiency of the allocation conditional on the distribution of fixed factors. To analyze this issue we introduce a variable cost efficiency index. The index is defined

as the ratio of the minimum variable cost of producing industry output, given the current distribution of fixed factors (age, capital, and productivity), to the actual variable cost of producing industry output. Firms are assumed to minimize variable cost given their fixed factors, so their actual variable cost of production is calculated as

$$C(Y_i, K_i, a_i, p_i, w_i) = \min_{L_i} \quad w_i L_i \quad s.t. \quad Y_i \leq L_i^{\beta_l} K_i^{\beta_k} e^{\beta_a a_i} e^{p_i} \tag{15}$$

where p_i is productivity as defined at the beginning of this section. The minimum total variable cost of producing industry output is calculated as the solution to

$$\min_{Y_1,\dots,Y_N} \quad \sum_{i=1}^{N} C(Y_i, K_i, a_i, p_i, w_i) \quad s.t. \quad \sum_{i=1}^{N} Y_i = Y \qquad . \tag{16}$$

The static efficiency index is calculated as the ratio of (16) to the sum of (15) across plants. The results from this calculation are presented in Table 9 where we have averaged the annual static cost efficiency index over several sub-periods.

Table 9 : Variable Cost Efficiency

(minimum cost of production divided by actual cost of production)

Years	Total	Interfirm	Intrafirm
1974–1977	.77	.85	.90
1978–1983	.67	.80	.84
1984–1986	.71	.79	.90
Mean	.72	.81	.88

Table 9 actually goes one step further than this. It decomposes the static variable cost index into two terms; a term providing a measure of the efficiency of allocation of output among plants within a firm (the intra firm index), and a term providing a measure of the efficiency of the allocation of output between firms (the inter firm index). Specifically the intra firm index is the ratio of the variable cost of production one would obtain if one allocated the *actual* firms' output efficiently among their own plants to the actual cost of production (obtained from 15). The inter firm component is the ratio of the minimum cost of production obtained from (16) to the cost of production obtained from efficiently allocating the existing firm distribution of output among the plants in the alternative firms (to the numerator of the intra firm index). Thus the product of the inter firm and the intra firm indices must equal the total index.

The total column of Table 9 shows that, not surprisingly, the static efficiency index declined in the 1978-1983 period, the period when the industry was undergoing the restructuring induced by the changes in the regulator environment. It did increase again after deregulation, but not to the level it had achieved in the pre 1978 period. All movements in the static efficiency index are caused by movements in the inter firm component of the index, the intra firm component was essentially constant at the high level of .9 throughout the period.

The more competitive structure that emerged after deregulation seems to have generated an inter firm allocation of output that is less efficient, *conditional* on both the total output produced by the industry and on the existing joint distribution of fixed variables, than the output allocation prior to deregulation. The lesson here is that more concentrated industry structures may well allocate output among existing plants in a more cost effective manner. The benefits from competition come from either less restrictive output practices, a reallocation of fixed factors towards more productive enterprises, or increases in average productivity growth. We now turn to an investigation of the latter two possibilities.

Recall that while the static variable cost efficiency index seems to have fallen after deregulation, the aggregate industry productivity figures increased following both periods of regulatory change. To see what is behind this set of results it

is helpful to decompose the productivity figures in a slightly different way. Recall that our measure of industry productivity is a weighted average of plant-level productivity, with shares of industry output as weights, i.e.,

$$p_{it} = \sum_{i=1}^{N_t} s_{it} p_{it} \quad ,$$

where p_t is industry productivity at time t, p_{it} is plant level productivity, and s_{it} is plant i's share of output at time t. Now decompose p_t into a sum of two terms as follows

$$
\begin{aligned}
p_t &= \sum_{i=1}^{N_t} (\bar{s}_t + \Delta\, s_{it})(\bar{p}_t + \Delta\, p_{it}) \\
&= N\, \bar{s}_t\, \bar{p}_t + \sum_{i=1}^{N_t} \Delta\, s_{it} \Delta\, p_{it} \\
&= \bar{p}_t + \sum_{i=1}^{N_t} \Delta\, s_{it} \Delta\, p_{it}
\end{aligned}
\qquad (18)
$$

where

$$\Delta\, s_{it} = s_{it} - \bar{s}_t, \ and \quad \Delta\, p_{it} = p_{it} - \bar{p}_t \qquad . \qquad (19)$$

and $\bar{p}_t$ and $\bar{s}_t$ represent the unweighted mean productivity and the unweighted mean share, respectively.

   Table 10 presents data on the three terms from equation (18). Column 1 is the left hand side of the equation; industry productivity constructed as a weighted average of plant-level productivities. Column 2 is the *unweighted* average of plant-level productivity, $\bar{p}_t$. Column 3 provides the second term on the

right hand side of (18), the sample covariance between
productivity and output. The larger this variance, the higher
the share of output that goes to more productive firms and the
higher is industry productivity. Finally, the fourth column of
Table 10 gives the correlation coefficient between plant-level
capital and plant-level productivity.

Table 10

Year	1	2	3	4
1974	1.00	.91	.09	-.059
1975	.87	.81	.07	-.092
1976	.86	.78	.08	-.106
1977	.92	.86	.06	-.070
1978	1.00	.91	.09	-.036
1979	1.01	.96	.05	-.030
1980	1.07	.96	.11	-.008
1981	1.07	.90	.17	.037
1982	1.07	.93	.14	.010
1983	1.00	.92	.09	-.056
1984	1.05	.97	.08	-.072
1985	1.10	.89	.21	.036
1986	1.08	.90	.17	.050
1987	1.08	.86	.23	.120

The table helps us separate out the factors underlying the
increase in productivity in column 1. $\bar{\Omega}_t$ has not changed all

that much since 1979, but there has been a reallocation of output from less productive to more productive plants. It is this reallocation output, and not any increase in average productivity, that is driving the increase in productivity at the industry level. From the analysis of the static cost efficiency index above, we know that this reallocation of output to more productive plants is not a result of a more efficient allocation of variable factors of production conditional on the existing distribution of fixed factors. So it should be a result of a reallocation of capital towards the more productive plants. A complete analysis of precisely how this happened and of the effect of the various policy and environmental changes on that process would require us to fill in the details of the dynamic general equilibrium model that lies behind the adjustment process that occurred in this industry ! a task beyond the scope of this paper. We can, however, provide some reduced form evidence on the importance and the implications of the capital reallocation process.

Column 4 of Table 10 provides the correlation between capital and productivity. It has increased dramatically since the Consent Decree, and it increased substantially following the earlier regulatory changes also. In fact the only two years in which there was a perceptible drop in the capital-productivity correlation were 1983-84, the years when the adjustment to deregulation must have been greatest.

One can also see the impact of the reallocation of capital towards more productive plants in the analysis of exit behavior. The stopping rule that comes out of the dynamic behavioral model (equation 5) implies that whether or not a firm shuts down is a function of its productivity, capital stock, and age. The nonparametric estimation procedure uses this fact to derive the survival probabilities, but treats these probabilities as nuisance parameters, never examining them for their independent economic interest. Table 11 provides a simple probit analysis of survival probabilities with our estimates of productivity, capital, and age, as well as time dummies, as right hand side variables. The probits have the exit probability negatively related to both the firm's capital stock, and to the firm's productivity (though, as in the production function, age is insignificant and sometimes the wrong sign), with productivity being the most significant of the two variables. Also, there seems to be a clear effect of deregulation on the probability of exit. Conditional on any triple for the state variable, that probability seems to have gone up after 1980. So one mechanism for the reallocation of capital that facilitated the increase in aggregate productivity that accompanied deregulation seems to have been an increase in the rate of shutdown of unproductive plants.

Table 11

Probit Models of Exit Probabilities[*]
(standard errors in parentheses)

	1	2	3
Intercept	-1.22 (.14)	-.613 (.260)	-.556 (.266)
Productivity	-.252 (.063)	-.234 (.064)	-.240 (.065)
Age		.007 (.006)	-.008 (.006)
Capital		-.081 (.031)	-.095 (.032)
D2			-.353 (.198)
D3			.114 (.144)
D4			.469 (.138)
# Obs	1900	1900	1900
Log Likelihood	-329.90	-326.28	-314.74

* The dummy variables are defined as follows:
    Base period is 1974-1977,
    D2 = 1 for years 1978 to 1980, 0 otherwise
    D3 = 1 for years 1981 to 1983, 0 otherwise
    D4 = 1 for years 1984 to 1986, 0 otherwise.

Our results indicate that the changes that occurred in the
telecommunications industry in this period improved the
performance of the telecommunications equipment industry by
inducing a reallocation of capital from less to more productive

plants. Note that since this reallocation process seems to be greatly facilitated by entry and exit, an important part of it would not be picked up from the analysis of balanced panels (much less aggregate data). Nevertheless, it is this reallocation of capital, rather than some increase in either the efficiency of the allocation of variable inputs, or in average productivity, that seems to be behind the increase in productivity that followed the deregulation of the telecommunications equipment industry.

VI   CONCLUDING CAVEATS

We conclude with two related caveats. First we would like to emphasize that it is still too early to assess the full impact of deregulation on productivity in the telecommunications equipment industry. Our analysis suggests that the change in regulatory structure was followed by an increase in industry productivity generated by a reallocation of capital and a shift in production towards more productive plants. However, the long term question of the effect of the divestiture on productivity will also have to come to terms with its effect on R&D activity. Partly as a result of the tremendous success of research efforts at Bell Labs, AT&T's research subsidiary, the telecommunications network in the United States is the most sophisticated in the world. Our estimates indicate that there has not been an increase in average productivity since divestiture. However any

change in productivity that resulted from a change in the

structure of R&D in the industry after deregulation would

probably not manifest itself in the data until after 1987. On

this point we should note that when we take the RBOC's together

with AT&T their joint R&D expenditures and employment after

divestiture are not lower than the predivestiture levels of AT&T

(Noll, 1987). On the other hand it is still too early to know

how the changes in the structure of the industry has affected the

productivity of those R&D expenditures.

The second point is related, though more theoretical. What

seems to be clear from the data is that certain enterprises

generate more sales for given amounts of capital and labor

expenditures than others, and that differences in this sales

generating ability (which we call productivity) among plants are

highly serially correlated over time. This implies that

there   is an unobserved, serially correlated, state variable

that is a determinant of both survival probabilities and input

choices.

The way the model of Sections II and III deals with this

unobserved, serially correlated, state variable is to assume that

there is a one-to-one relationship between it and investment

conditional on the observed state variables of the problem (at

least on the subset of the data with $i_t > 0$). A more general model

than the one outlined here, say one that allowed for a separate

effect of the outcome of an R&D process on profits, and hence on

the investment decision, would be unlikely to generate such an invertibility condition without incorporating information on additional observables. We stopped where we did because of a combination of data availability and the fact that the framework presented here seemed rich enough to capture the nature of the restructuring that occurred in the telecommunications equipment industry during the period of our study. We do not doubt, however, that extensions to (or modifications of) our techniques may be necessary in order to come to grips with either different questions or different data sets.

The conceptual point we would like to emphasize is not that our solution ought always be used. Rather it is that the solution that *is* used to study changes in the performance of an industry should take into account the fact that different enterprises are differentially efficient in producing sales, and that though these efficiency differences do vary over time, they are highly serially correlated. A result of this serial correlation is that the efficiency differences themselves become determinants of the rates of expansion (or contraction) of plants. This makes them an integral part of the process by which markets adjust to changes in their environment. In our case it was differences in the extent to which this adjustment took place pre and post deregulation that was the major determinant of the pre and post deregulation differences in industry performance.

Appendix 1: The Data

The data be used in this study is an extract drawn from the Longitudinal Research Database (LRD) maintained at the Center for Economic Studies at the Bureau of the Census. The LRD contains all the data for manufacturing establishments collected by the Census of Manufactures in 1963, 1967, 1972, 1977, 1982, and 1987 , and by the Annual Survey of Manufactures for non-Census years from 1973 to 1986. The data is collected at the establishment level and includes detailed information on the inputs and output that characterize the production process. A more detailed description of the data and how we constructed the variables used in this analysis can be found in Olley (1991).

Telecommunications networks are composed of three broad categories of equipment. Terminal equipment is equipment that terminates a telephone wire at a customer's premises and includes such products as telephone sets, key telephone sets, facsimile machines, and modems. Transmission equipment, which carries the signal between terminal stations and switching centers, includes coaxial cable, microwave radio equipment, optical fiber, and communications satellites. Finally, switching equipment, which is the heart of the network, links the terminals of the telecommunications system. The main types of switching equipment are private branch exchanges (PBX) and central office switching centers. This study focuses on all three types of equipment with

the exception of transmission cable. Thus we do not include

plants that produce the various types of transmission media such

as copper wire, coaxial cable, or glass fibers.

In terms of the classification system used by the U.S.

Bureau of the Census, the telecommunications equipment industry

is made up primarily of those plants that are classified in SIC

industry 3661, Telephone and Telegraph Apparatus. The three 5-

digit product classes within SIC 3661 are 36611, switching and

switchboard equipment, 36613, carrier line equipment, and 36614,

other telephone and telegraph wire apparatus. This last 5-digit

product class includes such products as telephone sets, key

telephone sets, and telephone answering devices. In addition, a

subset of the plants from SIC 3663, Radio and Television

Communications Equipment, are included in the analysis.

The subset of plants added from industry 3663 are plants

that produce products within the 5-digit product class 36631,

communications systems and equipment, except broadcast. The

Bureau of the Census classifies fiber optics communication

equipment, microwave communication equipment, facsimile

communication equipment, and carrier line equipment, n.e.c. (not

elsewhere classified) in the product class 36631, but we wished

to include plants that produce these products in the analysis of

the telecommunications equipment industry. However, the product

class 36631 also includes military space satellites, amateur

radio communications equipment, and other products that we felt

should be excluded from the data set. Therefore, we had to take care to eliminate from the data set those plants that primarily produce products outside our definition of the industry.

Though our choice of product classes is as close as possible to the definition of the product market as we could get, it should be pointed out that, since we have pulled together data for plants in different four-digit SIC industries, comparison with published aggregates will be limited.

We now describe the variables used in the analysis. Unless otherwise specified, all variables are measured at the plant level and are taken from the Longitudinal Research Database maintained at the Center for Economic Studies at the Bureau of the Census.

Value added is defined to be total shipments, adjusted for changes in inventories, minus the cost of materials. Real value added is constructed by deflating output by a 4-digit industry output deflator and deflating the cost of materials by a 4-digit materials deflator. The deflators are taken from the PCS database as extended by Wayne Gray (1989). The *labor* variable is an hours variable constructed by taking the total compensation for labor, including all supplemental labor costs, and dividing the total by the production worker wage rate at the given plant.

 The *capital* measure used in the regression analysis is constructed using a perpetual inventory method, $K_{t+1} = (1!^*)K_t + I_t$. Since the capital data in the LRD is detailed enough to

allow one to distinguish between buildings and equipment, all
calculations of the capital stock are done separately for
buildings and equipment. Real capital is obtained by deflating
investment by a 4-digit industry new investment deflator taken
from the extended PCS data set. As suggested by Hulten and
Wykoff (1981) buildings are depreciated at a rate of .0361, and
equipment at a rate of .1179.

In order to construct the capital series using the perpetual
inventory method, we had to address two other issues. We needed
an initial capital stock, and we wanted to utilize the LRD data
on rentals and used equipment expenditures. The method of
dealing with the initial condition problem differed with the
information available on the plant. If the plant is first
observed in an ASM year we treated the plant as a new entry, and
assumed the entire book value of capital was put in place in the
previous year. If a plant is first observed in a census year, it
could have opened any time between the previous census and the
first observed census. As a result we calculated two estimates
of capital; the first assumes that the plant is new in the first
observed census year, and the second assumes that the entire book
value was put in place in the previous census year. The initial
capital stock used in the analysis was a simple average of these
two estimates. For plants first observed in the first year of
the LRD (1963) we took the book value in that year to be correct.

If a plant was renting capital, the rental value is capitalized and added to current year capital stock. The rental data is capitalized using rental rates for all manufacturing supplied by the Bureau of Labor Statistics. Interestingly, rentals seem to be more important for smaller plants than they are for large plants. Many small plants do not have any buildings on their books and are renting their factory. Many of the plants also report purchases of used equipment. In the calculation of the capital stock, used equipment is deflated using the new investment deflator and added to current capital. Finally, partly because of the sampling design, there were often missing years on the plants. We imputed the missing investment data by averaging the actual investment in the year just before the missing data with the investment in the year immediately following the gap. This allowed us to keep the historical information on the plant's capital.

Appendix 2: The Variance Covariance Matrix
of the Parameter Estimates

This appendix provides a consistent estimator for the variance covariance matrix of the estimator of the production function coefficients. It is based of the results in Pakes and Olley (1991), which, in turn, extends previous work by Newey (1991), and Andrews (1991b). For more detail the reader should consult those articles.

Let z be the vector of observables on a plant in the current and the following period (with the understanding that the second period values are zero if the plant liquidated in the second year), x$\mathbb{N}$=[k,a,t], and \$$\mathbb{N}$=[\$$_k$, \$$_a$, \$$_t$]. Then, denoting second period values of a variable by a + subscript, for any estimate of g=g(P,$\mathbb{N}$-x$\mathbb{N}$\$), P=P(i,a,k), and $\mathbb{N}$=$\mathbb{N}$(i,a,k), define the vector of functions

m(z, \$, \$$_1$, g, P, $\mathbb{N}$) = P$_+$[y$_+$!\$$_1$1$_+$!x$_+$$\mathbb{N}$\$!g(P,$\mathbb{N}$!x$\mathbb{N}$\$)]{!x$_+$+[Mg(P,$\mathbb{N}$!x$\mathbb{N}$\$)/M$\mathbb{N}$]x} .   (1)

For a particular value of (\$$_1$, g, P, $\mathbb{N}$), say (b$_1$, g$_n$, P$_n$, $\mathbb{N}$$_n$), the estimation algorithm chooses its estimate of \$, say b, by minimizing 2 n$^{!1}$ 3$_i$ m(z$_i$,b,b$_1$,g$_n$(P$_n$,$\mathbb{N}$$_n$!x$\mathbb{N}$b) 2 , where 2x2=x$\mathbb{N}$x. Now if

D(z, \$, \$$_1$, g, P, $\mathbb{N}$) = {!x$_+$+[Mg(P,$\mathbb{N}$!x$\mathbb{N}$\$)/M$\mathbb{N}$]x}{!x$_+$+[Mg(P,$\mathbb{N}$!x$\mathbb{N}$\$)/M$\mathbb{N}$]x}$\mathbb{N}$,   (2)

then it can be shown that at the true value of all of the
parameters,

$$D(z, \$, \$_1, g, P, \mathbb{N}) = E[\mathbb{M}m(z, \$, \$_1, g, P, \mathbb{N})/\mathbb{M}\$ * J_t , P_{t+1}=1].$$

Finally let

$$f^*(z, \$, \$_1, g, P, \mathbb{N}) = m(z, \$, \$_1, g\ P, \mathbb{N})$$

$$+ P_+\{!x_+ + [\mathbb{M}g(P, \mathbb{N}!x\$)/\mathbb{M}\mathbb{N}]x\{[y_+ !\$_1l_+ !x_+\mathbb{N}\$!g(\mathbb{N}-x\mathbb{N}\$)]$$

$$+ P_+\{!x_+ + [\mathbb{M}g(P, \mathbb{N}!x\$)/\mathbb{M}\mathbb{N}]x\{[\mathbb{M}g(P, \mathbb{N}!x\$)/\mathbb{M}P][P_+!P] \qquad (3)$$

$$+ P_+\{!x_+ + [\mathbb{M}g(P, \mathbb{N}!x\$)/\mathbb{M}\mathbb{N}]x\{[\mathbb{M}g(P, \mathbb{N}!x\$)/\mathbb{M}\mathbb{N}][y!\$_1l!\mathbb{N}]$$

$$+ C[y!\$_1l!\mathbb{N}]\{l!E[l^*i,a,k]\} ,$$

where $C=P_+l_+[y!\$_1l!\mathbb{N}]/E\{l!E[l^*i,a,k]\}^2$.

The actual variance covariance matrix of the parameter
estimates is obtained by letting $f=f^*!Ef^*$, and setting

$$V(\$, \$_1, g, P, \mathbb{N}) = E[f(z, \$, \$_1, g, P, \mathbb{N})f(z, \$, \$_1, g, P, \mathbb{N})\mathbb{N}], \qquad (4)$$

and

$$D(\$, \$_1, g, P, \mathbb{N}) = E[D(z, \$, \$_1, g, P, \mathbb{N})] \qquad (5)$$

and then computing

$$(D\mathbb{N}D)^{!1}DVD(D\mathbb{N}D)^{!1},$$

where all functions are evaluated at the true value of the
parameters ($\$, \$_1, g, P, \mathbb{N}$). A consistent estimate of the
variance covariance matrix is obtained by substituting (b, b_1,
g_n, P_n, $\mathbb{N}_n$) for ($\$, \$_1, g, P, \mathbb{N}$) in equations (1) to (3),
computing the sample analogues to the expectations in (3), (4),
and (5), and substituting these into (6).

Note that if we were to ignore the last four terms in (3)
(set them equal to zero), then this variance covariance matrix

would be identical to the variance covariance we would obtain if
we knew ($\$$, g, P, N), substituted there true values into the
definition of m(@) in (1), and set the resulting equation to
zero. The last four terms in (3) provide adjustments for the
fact that we use estimators of g, P, N, and $\$_1$, rather than their
true values.

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